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세계 주요 공항의 환경 효율성 분석에 관한 연구*

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Measuring Environmental Efficiency of International Airports: DEA and DDF Approach

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Abstract

This study measured the environmental efficiency of 21 international airports based on sustainability reports issued by each airport for 2018. As many sectors in the industry paid attention to social and environmental responsibilities, airport operators comprise one of the leading sectors that streamlined their facilities to become increasingly sustainable and environmental. Nevertheless, studies on the environmental operations of airports are insufficient compared with studies on economic or operational efficiency. Therefore, the current study aims to determine any possible improvement in the environmental inefficiency of airports with the utilization of directional distance function (DDF) and to examine operational efficiency with the application of the data envelopment analysis (DEA). The majority of airports have operated their facilities efficiently, but not all have effectively managed pollutants generated by airports. Furthermore, many airports can still potentially reduce CO_2 and water consumption. This study suggests several implementable environmental improvements to the aviation sector. Moreover, other industrial sectors may use the research as a benchmark for enhancing environmental efficiency.

Key words: World Airport, Environmental Efficiency, DEA, DDF, Efficiency Scores

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Ⅰ. Introduction

According to the International Civil Aviation Organization(ICAO), air cargo transports approximately 35% of world trade value (six trillion USD). From the beginning of air cargo in 1910, freight traffic has gradually increased and reached 58 million tons (t) in 2018 (ICAO, 2018). It means that the importance of the airport sector has also grown. The increased traffic and importance of air cargo may have advanced world trade; however, it has also exerted negative effects on the environment(Park et al., 2019; Kamal and Kutay, 2021). An airport operator is an important industry sector related to aviation, trade, infrastructure development, and business activities. With the increasing importance and influence of airports in various areas, several airports need to consider environmental challenges, such as CO2 emissions, noise and air pollution, and chemical spills (GRI, 2014). CO2 emissions have been a critical issue in climate change, especially at a time when mitigating climate change has become a significant global challenge to airport operators. The International Air Transport Association (IATA) announced that civil aviation takes responsibility for approximately 2% of the world's CO2 emissions as of 2019. For this decade, airport operators worldwide have gradually channeled their efforts to reduce CO2 emissions by implementing the Airport Carbon Accreditation program, which was launched in 2009. The program is under the Airport Council International(ACI) with 302 airports located in 71 countries currently joining the program. Accredited airports can participate in the program according to four levels of accreditation, namely, mapping (measuring of carbon footprint), reduction (reduced CO2 emissions), optimization (CO2 reduction), and neutrality (similar to optimization but with offset residual CO2). Moreover, many regions have been adopted Emissions Trading Schemes (ETSs) to control environmental pollution, and European Union (EU) ETS is the most comprehensive and influential (Efthymiou & Papatheodorou, 2019). In 2008, EU ETS announced to include aviation activities to reduce CO2 emissions of aircraft from 2012 with Directive 101/2008/EC(Meleo et al., 2016). This new law targeted all flights departing and arriving in the European Economic Area airports.

If IATA sets the goal, and ACI classifies the state of airports, then Global Reporting Initiative(GRI) offers specific directions to airports. Since 1997 GRI has provided sustainability reporting as an independent organization. It was first introduced and recognized as an international organization that formulates global sustainability reporting standards. The organization has developed additional sector content from the perspective of sustainable development. The airport sector is one among the 10 sectors, namely, construction and real estate; electric utilities; event organization; financial services; food processing; media; mining and metals; non-government organizations; oil and gas; and aviation. Sustainability reports using GRI standards contain figures related to the environment. Moreover, these reports show how airports manage pollutants, such as CO_2 emission, water consumption, waste disposal, electricity usage, and noise control. Notably, each airport's combination of pollutants is unique. Several studies on the efficiency of airports focus on the number of passengers, as the sector is passenger-focused. For example, the ICAO provides a list of the busiest airports worldwide based on passenger traffic. Accordingly, the current study focuses on a different perspective. The approach begins with the cargo traffic aspects of airports in various locations regarding environmental efficiency and inefficiency.

Efficiency analysis has been widely applied to overall industrial sectors, regardless of whether they are profitable, because many resources, especially natural resources, are limited. Considering the distribution of finite resources, this analysis aims to determine maximum output. Data envelopment analysis(DEA) is an effective analytical tool for measuring efficiency and is used to evaluate the performance of various entities(Cooper et al., 2010). Specifically, DEA is used to measure operating efficiency. Thus, this study aims to examine the influence of environmental factors, CO_2 emissions, and water consumption, on the operating efficiency of airports and the extent to which environmental impacts alter efficiency. Additionally, this study suggests the extent of reduction of the abovementioned pollutants. It broadens the target of airports given their various locations. Using the results, this study then adopts directional distance function(DDF) and indicates possible incremental amounts of desirable outputs, such as aircraft movement and air cargo traffic. The majority of airports focus on reducing these pollutants and improving environmental conditions at airports, which can be easily assessed by visiting their websites. Therefore, assessing the current environmental conditions and identifying opportunities for improvement in environmental aspects are crucial steps for airports in the future. This study aims to aid in identifying these opportunities and pollutants that hinder operating efficiency. Importantly, it offers suggestion on the amount of reductions of these pollutants. It intends to suggest possibilities for the selected international airports(n=21) in terms of CO_2 emission and water consumption by reinforcing and re-creating their environmental policies and activities.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on efficiency and the environment. Section 3 describes the methodology. Section 4 analyzes and interprets the results. Finally, section 5 presents the implications, limitations, and conclusions of the study.

II. Literature Review

1. Environmental Research in Airports

Although prior studies investigated the pollutant emissions of airports, the majority focused on one or more airports within one country. However, aviation has affected environments worldwide by emitting pollutants during landing and takeoff and in its operation of airport infrastructure. These environmental hazards affect not only human health but also the climate(Lee & Oh, 2010). Scholars in transport sectors have raised alarms about such environmental problems. For example, Stettler et al.(2011) conducted a study in the United Kingdom to determine the relationship between health and airport emissions. The author introduced a modified method after noting a discrepancy, that is, an underestimation of black and organic carbon particulates using the current method for measuring emissions(Stettler et al., 2011). As previously cited, the majority of airport-related studies are limited to passengers. Therefore, the current study is novel in that it explores the environmental challenges of airports worldwide. Moreover, previous studies focused on the calculation of other factors. For example, Jones et al.(2015) conducted actual measurements of accumulated dust on various runway locations using a magnet and compared them with those of aircraft emissions at different levels. The result demonstrated that engines, brakes, and tires emit unique minerals that may refer to magnetic fingerprints. The abovementioned studies indicate that CO_2 is the main airport emission, and presented the significance of the measurement. An aircraft emits pollutants, including CO_2; however, terminal buildings also consume energy and emit CO_2. Kilkis(2014) compared a general terminal building to four scenarios including green terminal building from the perspective of CO_2 emission reduction potential. The study found that approximately 657,000 trees should be sacrificed to build a new green terminal in Istanbul and made conclusions based on the laws of thermodynamics, that is, constructing a green terminal building may not offset its CO_2 emissions. Thus, the airport should work intensively on re-forestation and re-select its construction site.

Apart from the CO_2-emission related environmental approach to airports, water consumption is another environmental factor cited by GRI standards and active research fields. A group of scientists, Bieliatynskyi et al.(2018) formulated a system that can save water consumption in airports. They found an algorithm for an automatized system that optimized water consumption by reusing water. Although the authors found difficulty in formulating an algorithm to follow all stages, they purported that saving water is based on reusing it. Furthermore, Carvalho et al.(2013) investigated the water management systems in airports according to categories detailed explicitly in water reuse. Forms of water reuse are grouped into the use of rain and the reuse of greywater, seawater, and sewerage effluent. Lastly, Baxter et al.(2019) investigated the water management system at the Copenhagen airport focused on reusing water through sewerage treatment systems. The airport utilized two sewer systems for surface water and wastewater and implemented a water-saving plan similar to an aquifer thermal energy system.

Other studies covered the diversities of the environmental performance of airports. Chang & Yeh(2016) classified environmental activities, such as conserving energy, using light-emitting diode(LED) bulbs in terminals, upgrading the water drainage system, using electric transport, and conducting educational programs through interviews. They applied this classification to Taiwan Taoyuan International Airport. Ferrulli (2016) introduced the Green Airport Design Evaluation, which can be implemented since the beginning of airport infrastructure planning. This research also categorized environmental factors, such as noise, air quality, water use and pollu-

Table 1. Studies of airport efficiency

Researchers	Method	Target airports	Inputs	Outputs
Pels et al.(2001)	DEA (BCC)	34 airports in Europe	Terminal size, aircraft parking positions, check-in desks, baggage claims	Passenger movements
			Airport area, runways, runway length, aircraft parking position	Aircraft movements
Martin & Roman(2001)	DEA (CCR, BCC, SE)	37 airports in Spain	Labor, capital, materials	Aircraft movements, members of passengers, tons of cargo
Fernandes & Pacheco(2002)	DEA (BCC)	35 airports in Brazil	Area of apron, departure lounge, number of check-in counters, curb frontage, number of vehicle parking spaces, baggage claim area	Domestic passengers
Bazargan & Vasigh(2003)	DEA (CCR)	45 airports in the US	Operating expenses, non-operating expenses, number of runways, number of gates	Number of passengers, number of airport carrier operations, number of other operations, aeronautical revenue, non-aeronautical revenue, percentage of on time operations
Barros & Dieke(2007)	DEA (CCR, BCC, SE)	31 airports in Italy	Labor costs, capital invested, operational costs excluding labor costs	Number of planes, number of passengers, general cargo, handling receipts, aeronautical sales, commercial sales

tion, energy, waste, and biodiversity. In a similar manner, Baxter et al.(2014) conducted a case study in Munich airport regarding design and operation from the perspective of airport sustainability. They investigated energy, water, waste, air, and noise and emphasized waste, water, and noise as important environmental factors. In summary, the environmental factors of the airports in the abovementioned studies share common activities. Among them, the current study considers air and water to determine the relationship between environment and efficiency.

2. Efficiency Analysis in Airport industry

Studies on airport efficiency, particularly those that employ the DEA, have been widely and frequently conducted on airports. Pels et al.(2001) examined the efficiency of airports in Europe from 1995 to 1997 from the two aspects. The first was based on aircraft movement, whereas the second used passenger movement as outputs under the CCR assumption. Moreover, Martin & Roman(2001) evaluated 37 airports in Spain using three inputs, namely, labor, capital, and materials, and three outputs, namely, aircraft movement, number of passengers, and cargo(in tons). Fernandes & Pacheco(2002) analyzed 35 domestic airports in Brazil with six inputs and one output. Considering the number of inputs, the study only considered domestic passengers as output. In the United States, Bazargan & Vasigh(2003) categorized 45 airports as large, medium, and small airport hubs and combined financial and physical figures to obtain inputs and outputs under the CRS assumption. Lastly, Barros & Dieke(2007) mainly focused on the financial information of airports in Italy as input and numbers and euro as outputs using CCR, BCC, and scale efficiency (〈Table 1〉).

The majority of studies on airport efficiency have used various forms of DEA as tools for investigating airport efficiency. Those tools are typically composed of two stages to derive robust results. For example, Wanke et al.(2016) applied fuzzy-DEA(FDEA) and regression to 30 airports in Nigeria. FDEA precisely captured the vagueness of contextual input and output measurements, such as regulation, capacity, movement, labor cost, and trend and validate the results through regression. Chu et al.(2010) used two-stage correlative DEA to evaluate the production efficiency of nine airports in Asia with airport staff, number of cities navigated, total assets, number of gates and check-in counters, and GDP of the city as independent variables for Tobit regression. Similarly, Tsui et al.(2014) applied regression to determine the relationship of efficiency scores to variables, yearly trends, GDP per capita, number of international passengers, and operating hours. This study differed because it added international hubs, airport management, government control, hinterland population, and alliance membership airline as dummy variables. Moreover, other studies measured airport efficiency by considering the types of a flight delays as an undesirable output. Lozano & Gutiérrez(2011) used single slack-based measure(SBM) DEA and network DEA, which produced undesirable outputs at the first stage. Furthermore, Lozano et al.(2013) established the DDF concept to increase desirable outputs and decrease undesirable output. It also used DEA CCR and BCC and applied DDF to suggest further reductions in undesirable outputs and increase desirable outputs.

Ⅲ. Methodology

1. Data Envelopment Analysis(DEA)

DEA is a mathematical programming using nonparametric analysis and measures the relative efficiency of decision-making units (DMUs). As a nonparametric model, it is used to compare efficient states and current efficiencies of observed values on the basis of linear programming. DEA does not require a statistical assumption about the population of production functions but estimates the relations between inputs and outputs using given data (Lee & Oh, 2010). Moreover, it evaluates performance of a data set composed of entities called DMUs (Cooper et al., 2010). For example, a DMU_i of $i=(1,2,\ldots,n)$ can be represented vectors as (X_i, Y_i), where the observed inputs are $X_i = (x_{1i}, x_{2i}, \ldots, x_{mi})$, whereas $Y_i = (y_{1i}, y_{2i}, \ldots, y_{si})$ denote observed outputs. And m means the number of the input and s means the number of the output. To observe efficiency, DEA is built on the production possibility set(PPS). If a certain amount of input can produce a certain amount of output, then this combination of input and output would be producible. PPS is a collection of all possible combinations, where the set envelopment of DEA originates (Banker et al., 1984), as demonstrated by Equation (1):

$$T = \{(X, Y) | Y \geq 0 \ can\ be\ produced\ by\ X \geq 0\} \quad (1)$$

This concept is characterized by free disposability, that is, if (x,y) are producible, then all $\hat{x}$ and $\hat{y}$ that satisfy $\hat{x} \geq x$, $\hat{y} \leq \hat{y}$ will be producible (Lee & Oh, 2010). PPS also allows the assumption of two models of returns to scale, namely, constant returns to scale(CRS) and variable returns to scale(VRS). CRS assumes that all points, which are increased or decreased at the same ratio as an observed value, are producible. Alternatively, VRS enables an increase or decrease of returns to scale.

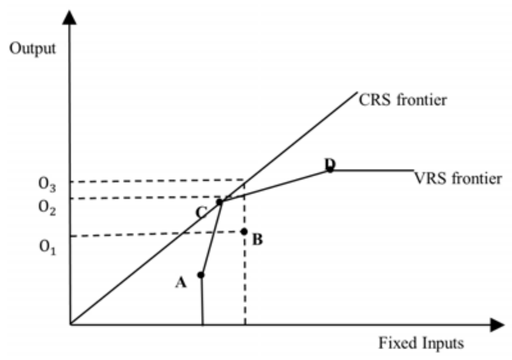

Figure 1. CRS and VRS assumptions

⟨Figure 1⟩ illustrates the efficiencies of each assumption. Each point in the graph is a DMU on the production frontier. Specific to this study, a DMU refers to an airport. Furthermore, the graph presents three types of efficiencies. First, efficient DMUs are plotted on the fitted line; but not all points of the line are fully efficient. Furthermore, efficient states can be divided into two types, namely, strong and weak. Weak efficiency points remain likely to improve by eliminating slacks. Lastly, there are inefficient DMUs. Although DMUs are not plotted right on the frontier, they are included in the PPS. In this case, increasing outputs or decreasing inputs would enable the movement of the inefficient plot close to the frontier to improve its efficiency. Points A, C and D in ⟨Figure 1⟩ reveal that they are efficient. However, point B should be moved forward to the frontier to become efficient.

The selection of the orientation regarding whether to retain or increase/decrease input or output is dependent on the features of the efficiency data set. Moreover, the orientation can be input- or output-oriented. Input-oriented CCR should reduce input and retain output at the same time, such that the minimized denominator can help improve efficiency. The envelopment model allows inefficient DMUs to benchmark the efficient ones. In contrast, the multiplier model withholds this information. Equation (2) presents the calculation of efficiency scores, which initiates input-oriented CCR:

$$
\begin{aligned}
& Min\theta_k \\
& s.t. \\
& \theta_k x_{ik} \geq \sum_{j=0}^{n} x_{ij}\lambda_j \quad (i=1,2,...,m) \\
& y_{rk} \leq \sum_{j=0}^{n} y_{rj}\lambda_j \quad (r=1,2,...,s) \\
& \lambda_j \geq 0 \quad (j=1,2,...,n)
\end{aligned} \tag{2}
$$

where x and y refer to Equation (1), and λ is the granted weight of each DMU. θ is an efficiency score, which indicates that the same level of output can be maintained even if the input vector is reduced to θx. Therefore, $(x-\theta x)$ would be the reducible amount of input. Conversely, output-oriented CCR elicits a ratio that requires the maximized output to increase the efficiency of data and fix inputs, as presented by Equation (3):

$$
\begin{aligned}
& Max\phi_k \\
& s.t. \\
& x_{ik} \geq \sum_{j=0}^{n} x_{ij}\lambda_j \quad (i=1,2,...,m) \\
& \phi_k y_{rk} \leq \sum_{j=0}^{n} y_{rj}\lambda_j \quad (r=1,2,...,s) \\
& \lambda_j \geq 0 \quad (j=1,2,...,n)
\end{aligned} \tag{3}
$$

However, Banker et al.(1984) presented a different assumption, which extended returns to scale to VRS (curved line in 〈Figure 1〉). The BCC model, on which this study is based, is relatively similar to the CCR model except that the formula constrains the sum of λ_j to 1. This constraint is imposed on the VRS condition and is derived as follows:

$$
\begin{aligned}
& Max\phi_k \\
& s.t. \\
& x_{ik} \geq \sum_{j=0}^{n} x_{ij}\lambda_j \quad (i=1,2,...,m) \\
& \phi_k y_{rk} \leq \sum_{j=0}^{n} y_{rj}\lambda_j \quad (r=1,2,...,s) \\
& \sum_{j=1}^{n} \lambda_j = 1;\ \lambda_j \geq 0 \quad (j=1,2,...,n)
\end{aligned} \tag{4}
$$

Equation (4) indicates the output-oriented BCC model. The consumed inputs are fixed as the outputs are maximized. In contrast to the CCR model, the efficiency scores of BCC models differ from those derived from input- and output-oriented models. Thus, the selection between the input- and output-oriented models is dependent on objectives, which, in the current study, is the infrastructure of airports worldwide as input at the DEA method and annual cargo traffic and operating revenues of airports as outputs. This study prefers the output-oriented method given that airport infrastructure is a relatively non-current asset and more likely to have capital dependent characteristics, which demands time and large capital investments. Moreover, one of the main objectives of the study is to maximize outputs, namely, air traffic cargo and revenue;

therefore, determining incremental output is more desirable.

2. Undesirable Outputs and Inefficiency

The DEA method measures the efficiency of DMUs and provides directions for less efficient DMUs to benchmark efficient ones. However, not all outputs produced by inputs are desirable. Many undesirable outputs are inevitably produced, which are called by-products, such as, pollutants, refunds, defaults, accidents, corruption, and crime. For example, suppose that a person makes breakfast with a sunny-side-up fried egg as the desirable output and the broken egg shell, which is considered food waste, as the undesirable output. Profit organizations that pursue profit maximization continuously produce desirable outputs to maximize efficiency despite the accompanying undesirable outputs. This characteristic of desirable and undesirable outputs is called null-jointness (Lee & Oh, 2010), which can be briefly described as undesirable outputs that accompany desirable outputs. Equation (5) formalizes this concept as follows:

$$If\ (x,y,b) \in P \text{ and } y=0,\ then\ b=0 \qquad (5)$$

where x, y, b and P denote input, desirable output, undesirable output, and the PPS, respectively.

Although producing undesirable outputs is difficult to avoid, desirable outputs should be increased to offset the equation. Färe et al.(1989) proposed two assumptions on disposability, namely, weak and strong disposability, which are dependent on whether the output is desirable or undesirable. Outputs under weak disposability can be reduced proportionally, whereas strong disposability enables nonproportional reduction. Moreover, Färe et al.(1989) insisted that negative outputs can be weakly disposable; however, positive outputs do not need this assumption and can assume free disposability. According to the DDF in terms of output, let (y, b) imply direction. Such a direction indicates that DDF increases and decreases desirable and undesirable outputs, respectively(Chung et al., 1997). Equation (6) defines the DDF for calculating inefficiency:

$$\vec{D}(x,y,b;g_u,g_b) = \max\beta : (x, y+\beta g_u, b-\beta g_b) \in P(x) \qquad (6)$$

where g denotes direction vector $g=(g_u,g_b)$ and points the direction toward which desirable and undesirable outputs should move.

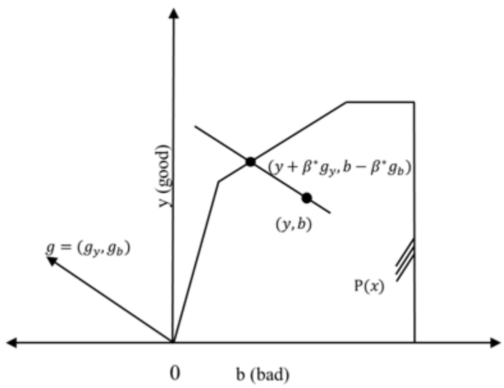

Figure 2. Directional output and distance function

source : Färe et al. 2007.

In ⟨Figure 2⟩, the vector indicates that positive outputs should be increased, whereas negative outputs should be mitigated. Therefore, both outputs are considered asymmetric. Moreover, optimal β is feasibly maximized when the increase and decrease in the quantities of vectors g_y and g_b are identical (Färe et al., 2007).

Equation (7) presents the following linear programming calculation to measure the inefficiency of DMU_k.

$$\overrightarrow{D}(x,y,b;g_y,g_b) = \max\beta$$
$$s.t.$$
$$\sum_{j=1}^{n} x_{ji}\lambda_j \le x_{ki} \quad (i=1,2,...,m)$$
$$\sum_{j=1}^{n} y_{jr}\lambda_j \ge y_{kr} + \beta g_{jr} \quad (r=1,2,...,s)$$
$$\sum_{j=1}^{n} b_{jp}\lambda_j = b_{kp} - \beta g_{bp} \quad (p=1,2,...,q)$$
$$\lambda_j \ge 0 \quad (j=1,2,...,n) \tag{7}$$

Equation (7) presents two options, which may differ according to whether the negative outputs are regulated (Färe et al., 2007). This study observed that airports and environment-related organizations continue to track and target low emissions. Therefore, this study employed the undesirable output regulated model. As such, the method is expected to demonstrate the environmental inefficiency of each airport based on CO_2 and water consumption. Moreover, expanding and contracting the desirable and undesirable final outputs would guide airports in identifying efficient production points.

3. Data Collection

The DEA model enables the identification of the optimal performance from of a set of multiple DMUs and the calculation of relative efficiencies(inefficiencies) of the other less efficient DMUs to efficient DMUs. To determine valid efficiencies, the number of DMUs should be at least more than twice of the total inputs and outputs(Fitzsimmons & Fitzsimmons, 1994). Moreover, Boussofiane et al.(1991) suggested the use of multiple number of input and output as the minimum number of DMUs. In general, scholars recommended the use of more than three times the number of inputs and outputs (Banker et al., 1989; Li et al., 2021; Seo et al., 2012). Therefore, the current study followed the last suggestion.

In the study, the DMUs are the selected airports that are mainly highly ranked in terms of international cargo traffic. Moreover, they are considered the world busiest airports as per passenger traffic standards, which suggest that more meaningful results can be obtained. The study focuses on the operating efficiency of these airports as well as their environmental factors. As such, managing and controlling environmental activities are important prerogatives for airports. To investigate the relationship between undesirable environmental outputs and total efficiencies of the airports, DMUs (i.e., airports) should provide data on their environmental performance. Therefore, airports that publish sustainability or environmental reports or at least offers environmental information were selected as DMUs. Thus, the study selects a total of 21 airports located in various countries.

Among the 21 airports, 11 are top-ranked airports for 2018 based on international cargo

Table 2. Data set including inputs and outputs for DEA method

DMU	Input			Environmental Factors		Outputs	
IATA code	Runway	Gate	Terminal	CO_2*	Water**	Movement	Cargo***
HKG	2	90	2	160,330	383,000	427,766	5,017,631
ICN	2	111	2	241,667	2,404,367	387,497	2,857,845
DXB	2	37	3	448,423	44,372	408,251	2,641,383
NRT	2	175	3	1,035,312	1,248,180	256,821	2,198,012
DOH	2	61	1	181,411	5,100,000	232,917	2,163,544
SIN	2	159	4	162,229	3,485,422	386,000	2,154,900
FRA	4	111	2	188,631	2,193,000	512,115	2,044,740
AMS	6	165	6	33,628	1,223,461	499,444	1,716,498
LHR	2	131	5	26,246	2,378,395	475,624	1,684,220
BKK	2	120	3	258,018	10,600,000	369,474	1,453,064
LAX	4	128	9	91,000	1,915,418	707,833	1,375,124
PEK	4	150	3	132,479	1,888,700	614,022	2,074,005
ATL	5	192	2	44,732	1,327,821	895,682	693,790
DEL	3	80	3	107,246	1,521,012	493,958	1,031,659
DFW	7	182	5	38,529	4,731,765	667,213	918,130
CGK	2	70	3	86,589	84,254	447,390	953,606
BNE	2	68	2	39,910	1,363,000	212,006	129,220
MUC	2	258	2	102,480	986,580	413,000	374,800
BOM	2	72	2	102,145	1,400,000	320,689	906,321
SYN	3	25	3	87,888	530,480	348,522	530,480
AKL	2	65	2	8,619	187,258	178,775	187,258

Source: Annual reports of each airports
Notes: *Measured in Metric ton(MT), **Measured in Cubic meter(m^3), ***Cargo=Measured in Metric ton(MT)

traffic. Specifically, five airports disclose their environmental information and are the world's busiest airports for 2018, whereas another five airports publish GRI reports with consideration of continental balance (no airport is situated in the Oceania area) and sustainability reports. These airport operators view the environment as one of the key issues among economic, environmental, and social categories. Among the abovementioned environmental aspects, this study used CO_2 emission and water consumption as intermediate factors.

According to the airport carbon and emissions reporting tool of the ACI, airport emissions are grouped into three categories, namely, scope 1 (emissions owned or controlled by the airport operator), scope 2 (emissions generated off-site due to electricity and heating or cooling purchased by the airport operator), and scope 3 (emissions owned or controlled by airport tenants

Table 3. Results of DEA-CCR, BCC and scale efficiency

Rank	IATA	CCR score	Rank	IATA	BCC score	Rank	IATA	Scale efficiency
1.	HKG	1	1.	HKG	1	1.	HKG	1
2.	DXB	1	2.	DXB	1	2.	ICN	1
3.	LHR	1	3.	DOH	1	3.	DXB	1
4.	ATL	1	4.	LHR	1	4.	NRT	1
5.	CGK	1	5.	LAX	1	5.	SIN	1
6.	SYD	1	6.	ATL	1	6.	LHR	1
7.	MUC	0.9655	7.	CGK	1	7.	BKK	1
8.	DOH	0.9415	8.	SYD	1	8.	ATL	1
9.	ICN	0.9059	9.	MUC	0.9655	9.	CGK	1
10.	FRA	0.8791	10.	DEL	0.9079	10.	MUC	1
11.	DEL	0.8689	11.	ICN	0.9059	11.	SYD	1
12.	SIN	0.8392	12.	FRA	0.8990	12.	FRA	0.9779
13.	BKK	0.8284	13.	BOM	0.8423	13.	PEK	0.9613
14.	LAX	0.8039	14.	SIN	0.8392	14.	DEL	0.9570
15.	PEK	0.7927	15.	BKK	0.8284	15.	DOH	0.9415
16.	BOM	0.7899	16.	PEK	0.8246	16.	BOM	0.9378
17.	DFW	0.6284	17.	DFW	0.8203	17.	BNE	0.9230
18.	NRT	0.5786	18.	AMS	0.6588	18.	AKL	0.9116
19.	BNE	0.5285	19.	NRT	0.5786	19.	LAX	0.8039
20.	AKL	0.4497	20.	BNE	0.5726	20.	DFW	0.7661
21.	AMS	0.4322	21.	AKL	0.4933	21.	AMS	0.6560

Source: Authors

and stakeholders who work at or near the airport). 〈Table 2〉 presents airport infrastructure as the input (no adjustment made after 2018) and cargo traffic as the output. The generated aircraft movement for 2018 is designated as a nondiscretionary input. According to the definition of ICAO, aircraft movement denotes takeoff or landing and arrival and departure as two movements (airport traffic). The environmental factors that are expected to influence operating efficiency are total water consumption amount(m^3) and CO_2 emissions(t), which compose scopes 1 and 2, respectively.

Ⅳ. Results and Discussions

For all efficiency measurements using DEA, inputs refer to the physical facilities of airports, such as the number of runways, gates, and terminals. These facilities are difficult to adjust because additional structures require specific amounts of financial investment and time. Outputs, such as aircraft movements and cargo traffic, are adjustable and more profitable if expanded. Thus, we applied the output-oriented method.

The left panel in ⟨Table 3⟩ presents the output-oriented and CRS constraints applied to the analysis. As the study is output-oriented, additional improvements were observed in the outputs. These improvements suggest that not all airports are thoroughly efficient in their operation. The Hong Kong International Airport(HKG), Dubai International Airport(DXB), London Heathrow Airport(LHR), Hartsfield–Jackson Atlanta International Airport(ATL), Soekarno–Hatta International Airport(CGK), and Sydney Kingsford Smith Airport(SYD) are efficient under the CRS assumption. In addition, these airports do not require a reduction of slacks, which renders them strongly efficient. Narita International Airport(NRT) has one of the top international cargo traffic records for 2018. Unexpectedly, however, it ranked as the fourth inefficiently operating airport. To increase its efficiency, NRT should reduce its gates to 72 and increase airport movement by 187,043 times. Expanding cargo traffic by 1,600,811 t is another possibility. Lastly, Amsterdam Airport Schiphol(AMS) displayed the lowest efficiency at 0.4322 under the CRS assumption. It ranks as the 13th busiest airport in terms of international cargo traffic.

The middle panel in ⟨Table 3⟩ indicates the results of data analysis using the output-oriented model under the VRS assumption. Notably, two airports were added as efficient under this assumption, namely, Hamad International Airport(DOH) in Qatar and Los Angeles International Airport(LAX) in the United States. The six other airports considered efficient are similar to those under the CRS assumption. In general, the results under the VRS assumptions are similar to those under the CCR assumption. However, noticeable differences in scores are observed between the CCR and BCC models. LAX exhibits the largest difference, where 0.8039 is relatively inefficient under the CRS assumption. However, it becomes one of the most efficient airports under the VRS assumption. Although the Dallas/Fort Worth International Airport(DFW) holds the same rank under the CCR and BCC assumptions (17th), its score increased up to 0.2 point. Moreover, although DOH and Chhatrapati Shivaji Maharaj International Airport(BOM) are considered inefficient, their scores increased by more than 0.05 point compared with other airport, who maintained the same score or displayed minor changes in the score.

After analysis using the CCR and BCC models, the study obtained scale efficiency(SE) by calculating the scores of the two models. Equation (8) displays the calculation for SE:

$$SE = \frac{\theta_k^*(CCR)}{\theta_k^*(BCC)} \tag{8}$$

Therefore, SE denotes the ratio of the distance between the CCR and BCC values. Avkiran(2001) defined SE as the decomposition of technical efficiency scores (CCR) divided into pure technical (BCC) and scale efficiencies. In general, the efficiency scores of under the VRS assumption is larger than those under the CRS assumption. Therefore, the value of SE should be distributed from 0 to 1 and should not exceed 1. When the SE score is close to 1, no efficiency loss is observed using the scale. Applying Avkiran(2001) to the selected airports, if the SE score is low, then airport expansion will require long-term planning. Conversely, if pure technical efficiency indicates inefficiency, general short-term improvements can be made because the airport does not need to change its scale. For example, Incheon International Airport(ICN), NRT, Singapore Changi Airport(SIN), Suvarnabhumi Airport(BKK), and Munich Airport(MUC) are inefficient in terms of CCR and BCC analyses. However, their SE score is 1, which indicates inefficient operation but no loss in scale perspective. Conversely, although LAX displays efficient operation, it should enlarge its scale in the long term. DFW and AMS are inefficient in operation or size relative to other airports, which is in contrast with the fact that both rank high in terms of cargo and passenger traffic.

Table 4. Directional distance function application

DMU		Reduced undesirable outputs		Improved desirable outputs	
IATA code	β	CO_2*	Water**	Movement	Cargo***
HKG	0.0000	160,330	383,000	427,766	5,017,631
ICN	0.5022	120,297	1,196,844	582,106	4,293,115
DXB	0.0000	448,423	44,372	408,251	2,641,383
NRT	0.7865	221,036	266,482	458,812	3,926,756
DOH	0.5899	74,392	2,091,381	370,321	3,439,873
SIN	0.5228	77,414	1,663,205	587,805	3,281,506
FRA	0.5008	94,170	1,094,805	768,568	3,068,690
AMS	0.0000	33,628	1,223,461	499,444	1,716,498
LHR	0.0000	26,246	2,378,395	475,624	1,684,220
BKK	0.8052	50,268	2,065,122	666,966	2,623,038
LAX	0.3359	60,438	1,272,123	945,560	1,836,961
PEK	0.3554	85,397	1,217,467	832,242	2,811,095
ATL	0.0111	44,236	1,313,097	905,614	701,483
DEL	0.4737	56,438	800,436	727,969	1,520,405
DFW	0.0000	38,529	4,731,765	667,213	918,130
CGK	0.0000	86,589	84,254	447,390	953,606
BNE	0.5855	16,542	564,926	336,141	204,882
MUC	0.4863	52,639	506,762	613,860	557,082
BOM	0.5477	46,196	633,162	496,344	1,402,751
SYN	0.3866	53,913	325,414	483,249	735,546
AKL	0.0000	8,619	187,258	178,775	187,258

Source: Authors

Notes: *Measured in Metric ton(MT), **Measured in Cubic meter(㎥), ***Cargo=Measured in Metric ton(MT)

This study considers negative environmental factors as undesirable outputs. As the best solution for improving efficiency, desirable outputs, such as aircraft movement and cargo traffic, should be maintained or increased and undesirable outputs should be minimized at the same time. By adopting the DDF, efficiency can be improved, that is, maintaining or decreasing CO_2 emissions or water consumption. Airport infrastructure is assigned as a nondiscretionary variable. This variable prevents airports from improving efficiency by shutting down runways, terminals, and gates, which is the least desirable solution for airports. Therefore, the direction vector denotes that all inputs should be 0 (Lozano et al., 2013).

〈Table 4〉 provides a list of airports considered inefficient and a list of possibilities for improving and reducing desirable and undesirable outputs, respectively. Beta (β) refers to values considered inefficient. In 〈Figure 2〉, if an observed point is located on the frontier, then its value is 0. When β is larger than zero ($\beta > 0$), then the observed point is inefficient and not located on the frontier. β converted into a percentage (β*100%) can increase the desirable output (i.e., 1+(β*100%) and decrease the undesirable output (i.e., 1-(β *100%) to be considered efficient.

In addition, 〈Table 4〉 indicates that seven airports are environmentally efficient because they do not require adjustment of desirable and undesirable outputs. This finding suggests that these airports do not need to reduce water use and CO_2 emissions relative to other airports. The environmentally worst airport is BKK because its desirable outputs can be improved by approximately 180%, whereas pollutants can be reduced by 20% relative to its current state. NRT also displays a similar level of inefficiency to BKK. Thus, aircraft movement and cargo traffic can be increased by approximately 78%, and water use and CO_2 emissions can be reduced by 78%. In this particular order, DOH, Brisbane Airport (BNE), BOM, SIN, ICN, and Frankfurt Airport(FRA) can be improved by more than 50%; MUN and Indira Gandhi International Airport(DEL) by more than 40%; and Beijing Capital International Airport(PEK) and LAX by more than 30%. LAX is the most environmentally friendly airport due to only 1% less to be efficient.

Ⅴ. Conclusion

The environmental challenges of airports have paved the way for their responses to the demands of the times, such as issuing environmental or sustainability reports and advertising green practices on their websites and other media platforms. The objective of the study is to identify the aspects where airports impact the environment and provide suggestions for improvement. The result confirmed that various environmental factors, such as CO_2 emissions and water consumption, have practically influenced airport efficiency. Although these factors might have led to environmentally negative impacts from airports, they also positively influence operating efficiency. Thus, the increased allocation of resources may stimulate increments in productivity. In other words, longer working terminals and warmer and brighter terminal buildings may directly or indirectly influence the profits of airports as these aspects increase their attractiveness. However, the result was relatively unexpected but extremely enlightening as the study found that environmental pollutants influenced operational efficiency. Thus, we conclude the study by moving on to the next step and by pinpointing that the outputs that may cause pollution are indirect by-products of desirable outputs. In other words, pollutants are related to inefficiency but can be reduced by increasing desirable outputs. Moreover, 33% of the airports obtained 0 . As such, these airports cannot be improved, as indicated by their DDF values.

Detailed results indicate that HKG(Hong Kong), DXB(Dubai), LHR(United Kingdom), and CGK(Indonesia) are operationally and environmentally efficient in all aspects. Many significant airports obtained different efficiencies in terms of operation and sustainability. AMS ranked lowest in SE despite it being one of the most environmentally well-controlled airports. Moreover, Auckland Airport(AKL) displayed an extremely low operational efficiency at less than 50% but ranks first in terms of environmental efficiency. Similar to AMS and AKL, DFW exhibited a relatively large gap between the two efficiencies. The results for these airports imply that well-operating airports may not always match their environmental management abilities.

Another point of concern is the efficiency of the classification of the airports. The size of cargo traffic and busyness may not always indicate that airports are operating efficiently or that their scale fits their capacities. It is also the same as the airports officially issue the environmental information according to the GRI guidelines. This notion indicates that the environmental activities of airports that issue sustainability reports are not always better than those of airports that do not. Moreover, a consensus could not be reached regarding whether airports in Europe perform better in terms of the management of environmental factors than airports in Asia or vice versa. Moreover, airport location does not contribute to its efficiency. Although many airports follow the GRI guidelines, the contents and manner of presentation or publication of reports may vastly differ across airports. Therefore, collecting identical and unified data from all airports is difficult. For example, NRT report environmental emission values per person, whereas other airports present total values. The units used also varied, such as metric ton, cubic meter, or liter, for water consumption. Therefore, the study omitted airports with different or missing environmental factors. The same problems were observed for environmental factors and airport figures. If airports worldwide follow more unified standards for figures, then further studies would be much more meaningful and beneficial. Diversity in information was also noted for airport infrastructure. Although nearly all airports indicate the number of terminals, only a few disclose the size of these terminals. Availability of this information would enable scholars to draw meaningful results using terminal areas as input. However, despite the availability of this information about terminals and runways, a few airports further distinguish passenger terminals from cargo terminals and disclose the number of both terminals. For instance, out of 21 airports, only five disclosed the number of cargo terminals. Furthermore, although no airports distinguished the purpose of the runways, conducting detailed efficiency analysis with a focus on the number of cargo runways would influence the results. This study attempted to make the indication more valid through DEA and DDF stages, each stage has its implication. Nevertheless, the suggested improvements would only be beneficial for airports that disclosed environmental information. Thus, this information may be a useful resource for scholars and may provide airports with opportunities for improvement.

Furthermore, the results of the study could serve as a signal for airports that consider and vigorously improve their environmental activities. Although airports may promote and advertise their environmental achievements to the public, its actual environmental performance can be relatively lower. Thus, this study may inform these types of airports to review their activities. For instance, NRT in Tokyo is one of the airports with the highest environmental performance with an apparent objective to reduce CO_2 in the next 10 years. Therefore, it actively promoted its master plan for an eco-airport that uses LED lights, solar power panels, a Greenport Eco-Agripark, a recycling plant, and a rainwater treatment facility. However, the environmental efficiency NRT was relatively inefficient compared with other airports. This case implies that the number of activities may not always lead to optimal efficiency. Kilkis(2014) found that green terminals are no more greener after determining that much more environment had to be scarified to build those terminals. The case of NRT may be similar to that of Istanbul Airport in Kilkis(2014), who found that its approach to the environmental operation may slightly be in the wrong direction. Thus, this scenario is another point of view, that is, airports may require long-term planning before they can reach an environmental turning point. Regardless of perspective, this study provides airports with the suggestion to reconsider their environmental policies using the recommended points of improvement.

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세계 주요 공항의 환경 효율성 측정: DEA와 DDF를 중심으로

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국문요약

본 연구는 각 공항의 2018년 지속가능성 보고서를 바탕으로 21개 국제 공항의 환경 효율성을 측정하였다. 최근 다양한 산업 분야에서 환경 및 사회적 책임에 관심을 기울여왔는데, 특히 항공 분야의 경우 환경 친화적 및 지속가능성 운영에 관심을 보이는 선도적인 부문 중 하나이다. 그럼에도 불구하고, 공항의 환경적 운영에 관련된 연구는 경제적 또는 운영 효율성 연구에 비하면 매우 부족한 실정이다. 따라서 본 연구는 Directional Distance Function (DDF)의 활용을 통해 공항의 환경 비효율성에 대한 개선 여부를 알아보고, Data Envelopment Analysis (DEA)의 적용을 통해 운영 효율성을 측정하는 것을 목적으로 한다. 연구 결과, 주요 공항들은 설비를 효율적으로 운영하고 있으나, 그들 모두가 공항에서 배출되는 물질을 효율적으로 운영하지는 못했다. 게다가, 많은 공항은 여전히 잠재적으로 CO2와 물 소비량을 감소시킬 수 있는 개선의 여지가 존재하였다. 이를 통해 본 연구는 항공 분야에서 실행가능한 환경적 개선점을 제시하고자 하였다. 더 나아가서, 다른 산업 분야에서도 환경 효율성 개선을 위한 기준으로서 이 연구를 활용할 수 있을 것이다.

주제어: 세계 공항, 환경 효율성, 자료포락분석, 방향거리함수, 효율성 점수